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The structural roles of sectors and their contributions to global carbon emissions: A complex network perspective

Meihui Jiang [a, b, c], Xiangyun Gao [a, b, c, *], Qing Guan [a, b, c], Xiaoqing Hao [a, b, c], Feng An [a, b, c]

[a] School of Economics and Management, China University of Geosciences, Beijing 100083, China
[b] Key Laboratory of Carrying Capacity Assessment for Resource and Environment, Ministry of Natural Resources, Beijing 100083, China
[c] Key Laboratory of Strategic Studies, Ministry of Natural Resources, Beijing 100812, China

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ABSTRACT

Carbon dioxide (CO2) emissions have a significant impact on global climate change. Previous studies have mostly focused on the impact of economic performance of sectors on carbon emissions, however, there is a lack of information about the influence of the structural roles on the full industrial chain. This article first built global embodied carbon emission transfer networks from 2000 to 2015, combining multi-regional input-output analysis and complex network theory, to explore the structural characteristics and recognize the structural roles of sectors. Then, panel regression analysis was applied to quantify the contributions of the structural roles of sectors to their carbon emissions. The results first showed that there were significant scale-free network characteristics in the global embodied carbon emissions transfer networks. The majority of global carbon emission transfers was concentrated on a limited number of sectors over time. Moreover, the network analysis revealed that sectors played different roles with different levels of importance in the global embodied carbon emission transfer networks. The results also suggested that the carbon emissions of sectors related to economic activity were significantly determined by some structural roles in the global embodied carbon emission transfer networks. Degree-in, strength-out and closeness-out and betweenness had significant positive influences, while degree-out, strength-in and closeness-in had significant negative impacts. These results indicated that carbon emissions mainly were increased by the domestic markets rather than international trades. Thus, adjusting the domestic consumption structures can be helpful for global carbon emission reduction. It also indicated that carbon emissions were not only driven by direct production demand from downstream sectors, but also were significantly influenced by indirect production demand in the industrial chain. Therefore, reducing carbon emissions should be established in both the direct and the indirect relationships in the production process.

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1. Introduction

Carbon dioxide (CO2) emission, one of the most important greenhouse gas, has a significant impact on global climate change (Baccini et al., 2012; Broecker, 2007; Cox et al., 2013; Forkel et al., 2016; McKenzie et al., 2016; Schuur et al., 2015). Recently, more scholars focus on accounting embodied carbon emissions to assess the impact of human economic activities on the environment (Deng and Xu, 2017; Tang et al., 2017; Wu et al., 2016). Previous studies have well revealed the transfer patterns of embodied carbon emissions between different sectors and have identified the main contributors of carbon emissions, however, there is still a gap within the existing body of knowledge: the contributions of the structural roles of sectors within the full industrial chain to carbon emissions.

In the existing research, scholars typically use the economic performance of sectors, including labor, GDP, energy consumption and import and export, to analyze the impact of these sectors on carbon emissions (Al-mulali and Sheau-Ting, 2014; Islam et al., 2016; Kasman and Duman, 2015; Yang et al., 2018; Zhang et al., 2017a). These works generally lead to the same results, i.e., the industrial manufacturing sectors or energy-related sectors are always the most important contributors of carbon emissions. However, the truth is that in the complicated economic system, different economies all depend on each other. There are direct or indirect economic connections between different countries, regions and sectors. The carbon emissions of one sector do not only depend on its production size but also depend on the supply of raw materials

* Corresponding author. School of Humanities and Economic Management, China University of Geosciences, Beijing, China.
E-mail addresses: gxy5669777@126.com, gaoxy@cugb.edu.cn (X. Gao).

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from upstream sectors and the production demands of downstream sectors. Some sectors may have small production sizes, but they may still be essential drivers of carbon emissions due to their central positions in the economic system. Thus, the positions of sectors in the industrial chain may also play the important roles in terms of global carbon emissions. It is imperative to recognize the structural roles of sectors in the economic system and identify the significant influences of the structural roles on carbon emissions.

Previous studies on carbon emissions have mostly focused on accounting embodied carbon emissions using input-output analysis (Du et al., 2011; Fang et al., 2017; Shao et al., 2016; Sheng et al., 2016; Su and Thomson, 2016; Tang et al., 2017). Embodied carbon emissions contain all historic information of carbon dioxide in the economic system, including production, transportation and consumption. Compared with direct carbon emissions, embodied carbon emissions provide a more systemic perspective to track carbon dioxide in the economic system. Furthermore, multi-regional input-output analysis was recently applied to quantify embodied carbon emission transfers between different regions (Su and Ang, 2011, 2014; Sun et al., 2017; Zhang et al., 2014, 2017b; Zhong et al., 2015). Globalization makes it increasingly common that one economy exports its production to another (Tang et al., 2013; Zhao et al., 2010, 2016). The existence of trading turns the global economy into an intertwined and complicated network. Recently, some scholars have started to focus on the carbon emission in socio-economic network, including embodied carbon emission trading among different regions (Feng et al., 2013), and the carbon emission linkages between different regions (Chen and Chen, 2016; Fang and Chen, 2018).

The researches above essentially mainly describe embodied carbon transfers between two sectors and often focus on the carbon emission intensity of sectors (Su and Ang, 2015, 2017), lacking the power to identify the structural roles of sectors in the global embodied carbon emission transfer network. For structural analysis of networks, complex network theory provides a good solution. Many scholars have shown that the function of a network depends on its structure, and the performances of its agents are significantly determined by their positions in the network (Bandyopadhyay and Kar, 2018; Chen et al., 2015; Kang and Woo, 2017; Newman, 2003; Sorrentino, 2007). Since small-world characteristic and scale-free characteristic have been found in the social network analysis (Barabasi and Bonabeau, 2003; Watts and Strogatz, 1998), complex network theory has been widely applied to many fields, including economics, finance and trading (Gao et al., 2017; Guan et al., 2016; Hao et al., 2016; Jiang et al., 2017a, 2017b; Sun et al., 2018; Zhong et al., 2016). The existing literature has shown that the algorithms of complex network theory can effectively recognize the structural roles of nodes in theoretical and realistic networks. Recently, complex network has been used to uncover the structure characteristics of industrial ecology networks. The small-world property has been found in the indirect energy flow network in China and global embodied rare earths flow network (Sun et al., 2016; Wang et al., 2017). It has been also found that there are significant evolutionary features in the structure of global embodied energy flow network (Shi et al., 2017). Thus, this paper uses complex network theory to analyze the structural roles of sectors in the global embodied emission transfer network. Furthermore, we apply a panel regression model to analyze the impact of different structural roles of sectors on carbon emissions.

The major aim of this paper is to answer the following question: which structural roles of sectors have significant contributions to global carbon emissions? We first built the global embodied carbon emission transfer networks by combining multi-regional input-output analysis and complex network. Then, we identified the structural roles of sectors in the network based on complex network theory. Finally, the contributions of the structural roles of sectors on carbon emissions were quantified by building the panel regression model.

2. Data

2.1. Data sources

The global input-output tables and carbon emission data were retrieved from Eora (www.worldmrio.com) (Lenzen et al., 2012, 2013), covering the period from 2000 to 2015. Each global input-output table contains 189 countries (including Taiwan Area) and 26 sectors in each country.

2.2. MRIO table structure

By combining domestic technical coefficient matrices with multi-regional import matrices, all trade cooperation between different regions can be captured in an MRIO model. Therefore, the MRIO table provides a useful tool that can be used to investigate the inter-connections among sectors and regions. The structure of an MRIO table is shown in Table 1.

z_{ij}^{rs} denotes the intermediate input from sector i in region r to sector j in region s. f_i^{rs} represents the final products of sector i produced in region r and consumed in region s. ex_i^r denotes the exports from sector i in region r to other regions. p_j^s means the primary input of sector j in region s. v_j^s denotes the added value of sector j in region s. x_j^s is the total input of sector j in region s, and x_i^r means the total output of sector i in region r.

In MRIO tables from Eora, there are some satellite accounts. These satellite accounts contain non-monetary inputs into production, including energy and emissions. e_j^s contains the energy input or the emissions of sector j in region s. This paper focuses on accounting embodied carbon emissions, thus e_j^s here represents the carbon emissions of sector j in region s.

3. Methods

3.1. Embodied carbon emissions accounting

For sector i in region r, the balance of embodied carbon emissions is as follows (Chen and Chen, 2013; Chen et al., 2012):

$$e_i^r + \sum_{n}^{s=1}\sum_{m}^{j=1} \epsilon_j^s z_{ji}^{sr} = \epsilon_i^r \left(\sum_{n}^{s=1}\sum_{m}^{j=1} z_{ij}^{rs} + \sum_{n}^{s=1} f_i^{rs} \right) \quad (1)$$

where ϵ_i^r represents the embodied carbon emission intensity of sector i in region r. n denotes the number of regions, and m denotes the number of sectors in one region. Sector i in region r connects to the outside environment via importing direct carbon emissions e_i^r and importing embodied carbon emissions $\sum_n^{s=1}\sum_m^{j=1}\epsilon_j^s z_{ji}^{sr}$ through purchasing goods and service from other sectors. $\sum_n^{s=1}\sum_m^{j=1} z_{ij}^{rs} + \sum_n^{s=1} f_i^{rs}$ represents the total output of sector i in region r. Thus, $\epsilon_i^r(\sum_n^{s=1}\sum_m^{j=1} z_{ij}^{rs} + \sum_n^{s=1} f_i^{rs})$ represents the total embodied carbon emissions output of sector i in region r.

For the whole economic system, let Σ denote the embodied carbon emission intensity vector $(\epsilon_i^r)_{m\times m}^{n\times n}$. E is the direct carbon emission vector $(e_i^r)_{m\times m}^{n\times n}$. Z is the intermediate input matrix $(z_{ij}^{rs})_{m\times m}^{n\times n}$. Y is the diagonal matrix that contains the sum of the final demand and the intermediate output

Table 1
Multi-regional input-output table with extended environment account.

Input		Output			
		Intermediate output	Final demand	Export	Total output
		Region (1, 2, 3, …, n)	Region (1, 2, 3, …, n)		
Intermediate input	Region (1, 2, 3, …, n)	z_{ij}^{rs}	f_i^{rs}	ex_i^r	x_i^r
Primary inputs		p_j^s			
Value-added		v_j^s			
Total input		x_j^s			
Environment accounts		e_j^s			

$diag((\sum_n^{s=1}\sum_m^{j=1} z_{ij}^{rs} + \sum_n^{s=1} f_i^{rs})_{m\times m}^{n\times n})$. The aggregate matrix form of Eq. (1) can be deduced as:

$$E^* + Z^* \times \Sigma^* = Y \times \Sigma^* \tag{2}$$

where E^*, Z^* and Σ^* are the transposes of E, Z and Σ, respectively; thus, the embodied carbon emission intensity vector Σ can be solved as:

$$\Sigma = E \times (Y - Z)^{-1} \tag{3}$$

The embodied carbon emission intensity of sector i in region r is multiplied by its intermediate input to the other sectors; then, we can obtain the embodied carbon emissions of sector i in region r to sector j in region s:

$$emc_{ij}^{rs} = \varepsilon_i^r z_{ij}^{rs}, \quad \varepsilon_i^r \in \Sigma \tag{4}$$

According to our data source, the unit of direct carbon emissions e_i^r is Gg, thus, the unit of embodied carbon emissions emc_{ij}^{rs} would also be Gg.

3.2. Global embodied carbon emission transfer networks

3.2.1. Network construction

We included sectors in different regions as nodes. The edges between the different nodes are the embodied carbon emission transfers between sectors. The edges are all directed and weighted. The direction of an edge is based on the input-output relationship between the sectors. The weight of an edge is the volume of the embodied carbon emissions that one sector inputs to the other.

3.2.2. Structural roles of sectors in the network

3.2.2.1. Degree. In a network, nodes with many neighbor nodes usually have the universality of exchanging information with the others. In a complex network, the universality can be measured by degree. Because the network in this paper is directed, the degree should be classified into degree-in and degree-out. In this paper, the degree-in of one sector refers to the number of sectors that input embodied carbon emissions to it. Thus, we can define degree-in as the number of import partners. Relatively, degree-out can be defined as the number of export partners. Degree-in and degree-out are calculated as follows, respectively:

$$D_i^{in} = \sum_{j\in N_i} A_{j,i} \tag{5}$$

$$D_i^{out} = \sum_{j\in N_i} A_{i,j} \tag{6}$$

where N_i is the set of nodes connected to node i. $A_{j,i}(A_{i,j})$ is the adjacent matrix of the network. If there is an edge from node j (i) to node i (j), $A_{j,i}(A_{i,j}) = 1$; else, $A_{j,i}(A_{i,j}) = 0$.

3.2.2.2. Strength. The strength of one node denotes the total weights of the edges connected to it. In a directed network, the strength includes strength-in and strength-out. In this paper, strength-in reflects the total import volume of the embodied carbon emissions of one sector, and strength-out reflects the total export volume of the embodied carbon emissions of one sector. Strength-in and strength-out are calculated as follows, respectively:

$$W_i^{in} = \sum_{j\in N_i} w_{j,i} \tag{7}$$

$$W_i^{out} = \sum_{j\in N_i} w_{i,j} \tag{8}$$

where N_i is the set of nodes connected to node i. $w_{j,i}(w_{i,j})$ is the weight of the edge from node j (i) to node i (j).

3.2.2.3. Clustering coefficient. The clustering coefficient measures the probability that the adjacent nodes of a node are connected. In this paper, if one sector has a high clustering coefficient, there are close connections between its neighbors. Thus, here, the clustering coefficient measures the degree of connection of one sector's industrial collaboration partners. For a weighted network, the formula for calculating the clustering coefficient is (Barrat et al., 2004; Wolfe, 1994):

$$C_i^w = \frac{1}{s_i(k_i - 1)} \sum_{j,h} \frac{w_{i,j} + w_{i,h}}{2} a_{i,j} a_{i,h} a_{j,h} \tag{9}$$

where s_i is the strength of node i. $a_{i,j}$ represents the element of the adjacency matrix. k_i denotes the degree of node i. $w_{i,j}$ is the weight of the edge from node i to node j.

3.2.2.4. Closeness. The closeness of a node is defined by the inverse of the average length of the shortest paths to or from all other nodes in the network. In a directed network, closeness-out measures how many steps are at least required to access every other node from a given node, while closeness-in measures how many steps will be at least taken if one node wants to access other nodes. In this paper, closeness describes the transfer speed of embodied carbon emissions from one sector to the others or from the others to the one sector. Closeness-in and closeness-out are calculated as follows (Freeman, 1978), respectively:

$$Cc_i^{in} = \left[\frac{1}{N-1}\sum_{j\neq i} d(j,i)\right]^{-1} \tag{10}$$

$$Cc_i^{out} = \left[\frac{1}{N-1}\sum_{j\neq i} d(i,j)\right]^{-1} \tag{11}$$

where N is the number of nodes. $d(j,i)$ denotes the shortest path from node j to node i. $d(i,j)$ denotes the shortest path from node i to node j.

3.2.2.5. Betweenness. The betweenness of one node is defined by the number of shortest paths going through it. Betweenness usually measures the media capability of nodes in the network. In this paper, if one sector has high betweenness, it means that this sector has strong media capability. Betweenness is calculated as follows (Brandes, 2001; Freeman, 1978):

$$B_i = \frac{\sum_k^n \sum_k^n g_{jk}(i) \Big/ g_{jk}}{(n^2-3n+2)/2}, \quad j\neq k\neq i,\ j<k \tag{12}$$

where $g_{jk}(i)$ denotes the number of the shortest paths from node j to node k that pass through node ig_{jk} denotes the number of the shortest paths from node j to node k.

4. Results

4.1. Structural characteristics of global embodied carbon emission transfer networks

Due to the essential characteristics of the global input-output tables that we used in this paper, the original global embodied carbon emission transfer networks were nearly fully-connected networks. In a fully-connected network, the effectiveness of some algorithms are weakened in terms of detecting structural characteristics. Thus, it would be difficult to uncover the essential structural characteristics of network. To better analyze the structure of global embodied carbon emission transfer networks, it is necessary to filter unimportant connections. In this paper, we ranked edges by transfer volume of embodied carbon emissions. To keep important edges as much as possible, the edges that occupied 90% of the weights were remained in the final networks. Other edges only occupied 10% of weights. Therefore, filtering these edges would not seriously influence the essential structural features of global embodied carbon emission transfer networks. The final global embodied carbon emission transfer network in 2015 is shown in Fig. 1.

Table 2 presents the structural properties of global embodied carbon emission transfer networks by year. On average over the period from 2000 to 2015, 1691.63 sectors were connected by embodied carbon emission transfers with 11,331.13 links between sectors. The number of sectors in the networks has declined from 1822 in 2000 to 1614 in 2015. The density of networks, which indicated the degree of completeness in the connections between sectors, was 0.00047 on average, which was relatively low. The average path length which represents the mean distance between any pair of nodes in a network was 4.121 on average, which indicated a sector usually transferred its embodied carbon emissions to another sectors through a path that crossed 4 other sectors.

In recent research on network analysis, "Preferential attachment" always makes random network to evolve and become scale-free networks over time (Barabasi and Bonabeau, 2003). "Preferential attachment" means that the network is usually heterogeneous, the distribution of connections between nodes is very uneven: the most connections concentrate on a few nodes, while most nodes have only a few connections. It has been suggested that

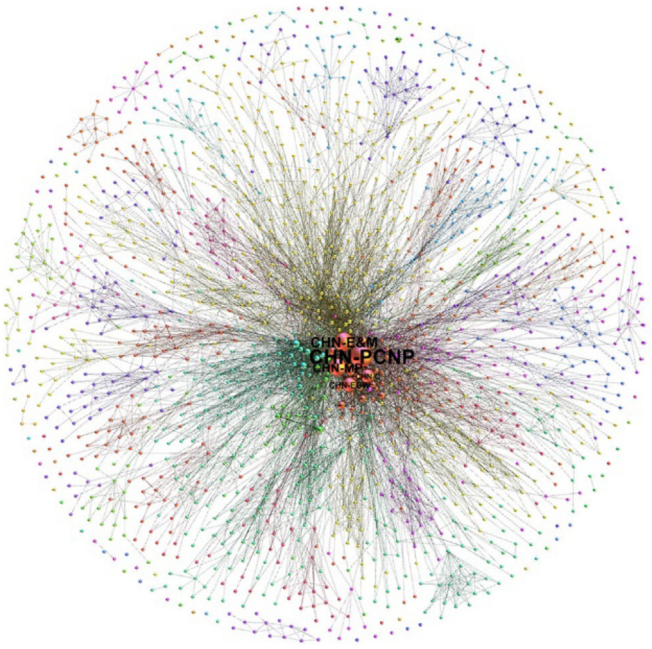

Fig. 1. Global embodied carbon emission transfer network in 2015.

most real-life networks are scale-free, which means that nodes are connected with preferential attachment. A scale-free network is defined that degree of the nodes follows power law distribution $p(k) \sim k^{-\alpha}$, where k is the degree of a node. It has been empirically found that most scale-free networks have α values between 2 and 3. As shown in Table 2, the values of α ranged from 2.722 to 3.04, indicating that the global embodied carbon emission transfer networks followed the power law of "complex system" characteristics found in scale-free networks.

4.2. Structural roles of sectors

The significant scale-free property indicates that a few sectors play important roles in the global embodied carbon emission transfer networks. Table 3 presents the values of each structural role of the top 10 sectors identified in 2015. Fig. 2 illustrates the evolution of structural roles of the selected sectors from 2000 to 2015.

The degree-in and degree-out values generally remained stable from 2000 to 2015 in Fig. 2 (a) and Fig. 2 (b). This stability means the degree of connection between sectors did not change a lot. Sectors have had stable importing and exporting partners during the 16-year period. The number of importing partners of some sectors has experienced a slight downward trend, like Re-export & Re-import in Germany, Petroleum, Chemical and Non-Metallic Mineral Products in China, and Electrical and Machinery in China. Meanwhile, the difference between the number of import partners of the top 10 sectors has become increasing smaller.

The values of strength-in and strength-out both had a significant upward trend from 2000 to 2015. This upward trend means the transfer volumes of embodied carbon emissions have increased during this period. Fig. 2 (c) and Fig. 2 (d) also showed that the volumes of imports and exports in these Chinese sectors all had downward trends after 2012. Most sectors which had significant decrease were Chinese sectors, including Petroleum, Chemical and Non-Metallic Mineral Products, Electrical and Machinery and Metal Products in Fig. 2 (c) and Electricity, Gas and Water, Petroleum, Chemical and Non-Metallic Mineral Products and Metal Products in Fig. 2 (d). It was mainly because that the Chinese government made a series of environmental protection policies after 2012, especially

Table 2
Structural properties of global embodied carbon emission transfer networks by year.

Year	No. of node	No. of edge	Average strength	Network density	Average path length	α
2000	1822	13,678	13,759.06	0.00057	4.205	2.969
2001	1824	13,253	14,208.67	0.00055	4.190	3.084
2002	1823	13,045	14,813.98	0.00054	4.167	3.070
2003	1783	12,808	16,100.01	0.00053	4.168	3.044
2004	1786	12,967	17,397.56	0.00054	4.082	2.973
2005	1763	12,356	18,806.71	0.00051	4.140	3.068
2006	1773	12,561	19,918.15	0.00052	4.078	2.960
2007	1707	11,614	22,007.01	0.00048	4.047	2.942
2008	1692	11,418	22,951.79	0.00047	4.018	2.925
2009	1599	9655	22,910.03	0.00040	4.140	2.975
2010	1575	9602	24,666.53	0.00040	4.095	2.948
2011	1567	9618	25,786.3	0.00040	4.098	2.897
2012	1564	9453	25,747.32	0.00039	4.130	2.722
2013	1548	9225	26,587.62	0.00038	4.130	2.738
2014	1626	10,226	23,190.37	0.00042	4.122	2.940
2015	1614	9819	22,840.37	0.00041	4.129	2.992
Average	1691.63	11,331.13	20,730.72	0.00047	4.121	2.953

Table 3
Structural roles of the top 10 sectors in 2015.

Rank	Degree-in		Degree-out		Strength-in		Strength-out	
	Sector	Value	Sector	Value	Sector	Value	Sector	Value
1	DEU-RE&RI	96	CHN-PCNP	175	CHN-PCNP	4,179,225	CHN-EGW	6,629,190
2	CHN-PCNP	82	CHN-MP	127	CHN-E&M	3,369,700	CHN-PCNP	5,179,472
3	CHN-E&M	78	CHN-E&M	127	CHN-MP	3,095,316	CHN-MP	3,365,415
4	USA-PCNP	72	USA-PCNP	109	CHN-EGW	2,349,725	CHN-E&M	2,354,624
5	USA-PA	69	USA-T	103	CHN-C	2,215,421	IND-EGW	1,671,814
6	USA-TE	62	DEU-RE&RI	80	CHN-TE	994,999.6	USA-EGW	1,573,949
7	CHN-C	60	RUS-PCNP	80	CHN-TWA	969,884	USA-T	1,493,058
8	USA-E&M	59	DEU-PCNP	79	USA-PCNP	953,828.5	USA-PCNP	1,086,103
9	JPN-PCNP	57	IND-PCNP	75	CHN-M&Q	864,101.6	CHN-T	1,057,041
10	NLD-RE&RI	57	CHN-TWA	60	CHN-EHO	790,518.6	CHN-M&Q	957,259.3
Rank	Closeness-in		Closeness-out		Clustering coefficient		Betweenness	
	Sector	Value	Sector	Value	Sector	Value	Sector	Value
1	DEU-RE&RI	4.63E-08	CHN-PCNP	4.80E-08	CHN-PA	1	CHN-PCNP	1
2	NLD-RE&RI	4.63E-08	USA-T	4.79E-08	USA-M&P	1	DEU-RE&RI	0.887
3	USA-TE	4.62E-08	USA-PCNP	4.79E-08	USA-PH	1	USA-T	0.501
4	CHN-E&M	4.62E-08	JPN-T	4.77E-08	GRC-PA	1	USA-PCNP	0.477
5	USA-PA	4.62E-08	DEU-RE&RI	4.77E-08	POL-PA	1	NLD-RE&RI	0.444
6	DEU-E&M	4.62E-08	RUS-PCNP	4.77E-08	USA-O	1	IND-PCNP	0.362
7	FRA-TE	4.61E-08	CHE-PCNP	4.77E-08	EGY-RT	1	DEU-E&M	0.361
8	ITA-TWA	4.61E-08	CHN-MP	4.77E-08	EGY-EHO	1	CHN-MP	0.358
9	CHN-EHO	4.61E-08	IND-PCNP	4.77E-08	PAK-PA	1	CHN-E&M	0.344
10	BEL-RE&RI	4.61E-08	DEU-E&M	4.76E-08	DEU-H&P	1	JPN-T	0.336

in relation to the overcapacity in heavy industries. Other sectors, like Petroleum, Chemical and Non-Metallic Mineral Products in USA in Fig. 2(c) and Electricity, Gas and Water, Transportation and Petroleum, Chemical and Non-Metallic Mineral Products in USA in Fig. 2(d), also have slight but consist decreases after 2012. These decreases were possibly caused by coal-to-gas switch policy in electricity generation sectors in USA.

The values of closeness-in and closeness-out were all very small. These small values mean the transfer speed of embodied carbon emissions was relatively slow. Some changes of sectors would reach other sectors or be reached by others slowly. According to Fig. 2 (e) and Fig. 2 (f), the values of closeness-in and closeness-out both had a significant downward trend from 2000 to 2015. This decline means the connections between the sectors were becoming looser, and the change of the sectors would take longer paths to influence others.

In 2015, the clustering coefficients of the top 10 sectors were all 1. This result indicates the neighbors of these sectors are all connected to each other. There were many local clusters in the global embodied carbon emission transfer network, so the connection degree in some local parts of the network was very high. From 2006 to 2008 in Fig. 2 (g), it can be seen that there were dramatic decreases in all of the top 10 sectors. This phenomenon was caused by the influence of the economic crisis. Many sectors lost their industrial cooperation partners.

According to Fig. 2 (h), the values of betweenness had various dramatic fluctuations from 2000 to 2015, ranging from 0 to 1. This result means that the media capacity of sectors was very unstable. In 2015, the most important media included Petroleum, Chemical and Non-Metallic Mineral Products in China, Re-export & Re-import in Germany and Transport in USA.

4.3. The contributions of structural roles of sectors to their carbon emissions

In complex network theory, the performance of a network is decided by its structure. Thus, in global embodied carbon emission transfer network, the structural roles of the sectors would significantly contribute to their carbon emissions. To test this hypothesis, we used panel regression analysis to examine the relationships between the structural roles of sectors and their carbon emissions. We chose the carbon emissions of each sector as the dependent

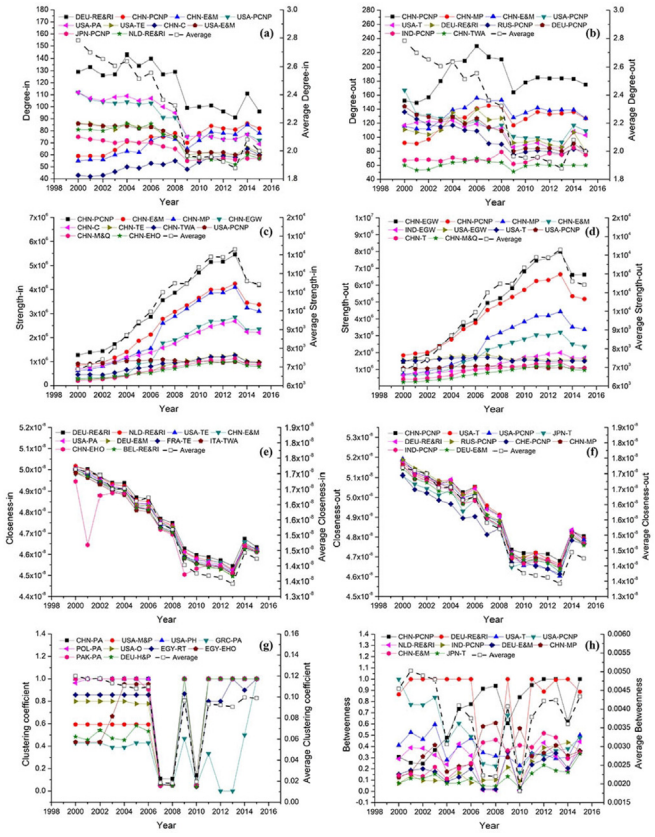

Fig. 2. The evolution of the structural roles of the top 10 sectors in 2000–2015.

variable, and we used strength-out, strength-in, degree-out, degree-in, clustering coefficient, closeness-out, closeness-in, and betweenness as the independent variables. Table 4 provides the descriptive statistics of all the considered variables. As we can see from Table 4, there were significant differences between the values of certain variables. Thus, to have horizontal comparisons between variables, before building the regression model, we should normalize all the variables to range from 0 to 1. The results of the unit root tests showed all normalized variables were stationary, and the cointegration tests showed there were cointegration relationships between the variables.

We respectively built the random-effect model, the fixed-effect model and the mixed-effect model. To choose the most appropriate model, we first conducted a Hausman test to determine if the fixed-effect model was preferred to the random-effect model. The Hausman test results (Table 5) suggested that the null hypothesis stating that there was a significant random effect should be rejected. Then, the Chow test (F test) was conducted to determine

Table 4
Descriptive statistics of the indicators.

Variables	Obs.	Mean	Max.	Min.	SD
Independent variable					
Degree-in	26,672	6.74	143.00	0.00	9.96
Degree-out	26,672	6.77	229.00	0.00	12.77
Strength-in	26,672	30,538.50	5,453,329.00	0.00	165,301.80
Strength-out	26,672	30,547.57	7,997,019.00	0.00	214,838.30
Closeness-in	26,672	4.29E-08	5.02E-08	0.00	8.62E-09
Closeness-out	26,672	4.30E-08	5.19E-08	0.00	8.82E-09
Betweenness	26,672	0.01	1.00	0.00	0.05
Clustering coefficient	26,672	1.47	129.00	0.00	4.85
Dependent variable					
Carbon emissions	26,672	18,153.82	5,893,473.00	0.00	138,850.90

Table 5
Hausman specification test.

Chi-Sq. Statistic	Chi-Sq. d.f.	Prob.
1936.4	8	0.000

Table 6
Chow test.

F Statistic	Prob.
19.74	0.000

whether the model should be a fixed-effect model or a mixed-effect model. The results (Table 6) showed that a fixed-effect model was more appropriate.

The results of panel regression analysis are presented in Table 7. The fixed-effect model showed high explanatory power, with an adjusted-R^2 of 0.695. The regression results showed that degree, strength, closeness and betweenness had significant contributions to the carbon emissions. Degree-in, strength-out, closeness-out and betweenness had significant positive influences, while degree-out, strength-in and closeness-in had significant negative impacts.

The regression results showed there were opposite relationships between the number of export partners and carbon emissions. Although some sectors have less trading partners, they still export significant embodied carbon emissions. This is mainly because currently the goods and service are mostly self-consumed in the domestic market in many countries, including China, USA, Japan and India (Deng and Xu, 2017). Compared to the sectors taking part in worldwide international trading, the sectors which mainly provided products for self-consumption usually had less export partners. However, these sectors usually produced plenty of carbon emissions. For example, the sectors which produced most carbon emissions usually included Electricity, Gas and Water, Transport and Construction in different countries (Deng and Xu, 2017; Zhao et al., 2016). The goods and service from these sectors mainly meet the demand of domestic market rather than international market. However, the carbon emissions produced by these three sectors accounted for 67.7% of total carbon emissions in 2015. This result indicated that carbon emissions mainly were increased by the domestic consumption, comparing with international trades. Thus, adjusting the domestic consumption structures can be helpful for global carbon emission reduction.

The results of panel regression analysis also showed strength-out had the greatest positive contributions to global carbon emissions among all structural roles. It is consistent with previous studies which have found that economies which had high carbon emission intensity usually were net embodied carbon emission exporters (Long et al., 2018). It is because these important embodied carbon emission exporters usually produced products which plenty of carbon emissions were embodied in and then inputted them to other sectors. In these production processes, they produced many carbon emissions. Conversely, sectors that imported many embodied carbon emissions from other sectors usually produced little carbon emissions, because most of the inputs that they need for their economic activities came from the other sectors. This result indicated that carbon emissions were mainly driven by direct production demand from downstream sectors. Thus, controlling the direct production demand from downstream sectors can help to significantly reduce carbon emissions.

Moreover, the results of panel regression analysis showed other structural roles, including closeness and betweenness, had weak but significant contributions to global carbon emissions. The relationships between closeness and carbon emissions indicated that the transfer speed of influence had significant impact on carbon emissions. If sectors can reach the other sectors very quickly, they

Table 7
Results of panel regression.

Variable	Panel regression analysis					
	Random-effect model		Fixed-effect model		Mixed-effect model	
	Coefficient	t-Statistic	Coefficient	t-Statistic	Coefficient	t-Statistic
Degree-in	0.049***	22.235	0.046***	19.192	0.093***	54.021
Degree-out	−0.102***	−44.890	−0.103***	−44.482	−0.095***	−38.414
Strength-in	−0.186***	−58.036	−0.168***	−51.505	−0.455***	−134.214
Strength-out	0.790***	238.090	0.766***	226.066	1.099***	329.906
Clustering coefficient	0.000	−0.160	0.000	0.184	−0.002***	−6.217
Closeness-in	−0.005***	−5.368	−0.005***	−5.164	−0.016***	−9.989
Closeness-out	0.005***	5.368	0.005***	5.136	0.017***	10.838
Betweenness	0.028***	20.160	0.027***	20.139	−0.032***	−11.169
Adj. R-squared	0.724		0.695		0.849	

Note: Level of significance: * is 10%, ** is 5%, and *** is 1%.

will produce more carbon emissions. This is because in the production chain, if sectors can quickly reach the other sectors, they usually are direct or indirect upstream sectors of many sectors, and can receive the production demand from downstream sectors very soon. Thus, these sectors should provide their products for others at the same time, so they usually produce a lot of carbon emissions. In the exchanges of carbon emissions, sectors, which are principle media, usually produce more carbon emissions. These sectors are passed by many carbon emission transfer paths. Hence, these sectors are important bridges of carbon emissions transfer, connecting upstream sectors and downstream sectors (Sun et al., 2016). The production intensity of sectors is influenced by the supply of the raw material from upstream sectors and by the production demand from downstream sectors. Thus, many carbon emissions are produced. The impacts of closeness and betweenness showed that indirect production demands in the full industrial chain can also significantly increase carbon emissions. Therefore, reducing carbon emissions should be established in both the direct and the indirect relationships in the production process.

5. Discussion and conclusion

In this paper, our major aim was to quantify the contributions of structural roles of sectors to their carbon emissions. We first built the global embodied carbon emission transfer networks combining multi-regional input-output analysis with complex network. Then, we identified the structural roles of sectors in the global embodied carbon emission transfer networks using complex network analytic approach. Finally, we applied panel regression model to examine the impact of the structural roles of sectors on their carbon emissions.

Scale-free network characteristics indicated that the global embodied carbon emissions transfer networks were concentrated on a small number of sectors with high connectivity. Given the slightly declining number of sectors connected by the exchanges of embodied carbon emissions, the coefficient of power law showed a similarly stable trend from 2000 to 2015. This stability suggested that most of the global carbon emission transfer were concentrated on a limited number of sectors during recent years. The network analysis also revealed that sectors played different roles with different levels of importance in the global embodied carbon emission transfer networks. Some sectors had many import partners, such as Re-export & Re-import in Germany, while some sectors had many export partners, such as Petroleum, Chemical and Non-Metallic Mineral Products in China. There were also some important importers, such as Petroleum, Chemical and Non-Metallic Mineral Products in China, and some important exporters, like Electricity, Gas and Water in China. Re-export & Re-import in Germany had high closeness-in, while Petroleum, Chemical and Non-Metallic Mineral Products in China had high closeness-out. These results mean that Re-export & Re-import in Germany can be easily reached by other sectors, and Petroleum, Chemical and Non-Metallic Mineral Products in China can easily reach to other sectors. Some sectors had a high clustering coefficient, which indicated that there were many local clusters in the global embodied carbon emission transfer network. Some sectors also had the important roles as transfer media, including Petroleum, Chemical and Non-Metallic Mineral Products in China, Re-export & Re-import in Germany and Transport in USA.

Panel regression analysis suggested that carbon emissions of sectors related to economic activity were significantly determined by some structural roles in the global embodied carbon emission transfer networks. Degree-in, strength-out and closeness-out had significant positive influences, while degree-out, strength-in, closeness-in and betweenness had significant negative impacts. The relationship between carbon emissions and the number of trading partners indicated that carbon emissions mainly were increased by the domestic markets, comparing with international trades. Thus, adjusting the domestic consumption structures can be helpful for global carbon emission reduction. Strength-out had the most important positive contribution to carbon emissions. This result means that carbon emissions were mainly driven by direct production demand from downstream sectors. Thus, controlling the direct production demand from downstream sectors can help to significantly reduce carbon emissions. Moreover, the impacts of closeness and betweenness showed that indirect production demands in the full industrial chain can also significantly increase carbon emissions. Therefore, reducing carbon emissions should be established in both the direct and the indirect relationships in the production process.

The main purpose of this paper is to analyze the contributions of structural roles of sectors to their carbon emissions, and provide the useful information for reasonably reshaping current industrial structures and reducing carbon emissions. The limitation of this paper is that our current work mainly focuses on the static analysis. The dynamic simulation aiming to reduce carbon emissions by adjusting the current structures of the global embodied carbon emission transfer networks will be discussed in the future.

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Appendix A

Table A
sectors and their codes.

Number	Sector	code
1	Agriculture	A
2	Fishing	F
3	Mining and Quarrying	M&Q
4	Food & Beverages	F&B
5	Textiles and Wearing Apparel	TWA
6	Wood and Paper	W&P
7	Petroleum, Chemical and Non-Metallic Mineral Products	PCNP
8	Metal Products	MP
9	Electrical and Machinery	E&M
10	Transport Equipment	TE
11	Other Manufacturing	OM
12	Recycling	R
13	Electricity, Gas and Water	EGW
14	Construction	C
15	Maintenance and Repair	M&P
16	Wholesale Trade	WT
17	Retail Trade	RT
18	Hotels and Restaurants	H&P
19	Transport	T
20	Post and Telecommunications	P&T
21	Financial Intermediation and Business Activities	FI&BA
22	Public Administration	PA
23	Education, Health and Other Services	EHO
24	Private Households	PH
25	Others	O
26	Re-export & Re-import	RE&RI

Table B
Countries and their codes.

Country	Code	Country	Code	Country	Code	Country	Code
Afghanistan	AFG	North Korea	PRK	Liberia	LBR	San Marino	SMR
Albania	ALB	DR Congo	COD	Libya	LBY	Sao Tome and Principe	STP
Algeria	DZA	Denmark	DNK	Liechtenstein	LIE	Saudi Arabia	SAU
Andorra	AND	Djibouti	DJI	Lithuania	LTU	Senegal	SEN
Angola	AGO	Dominican Republic	DOM	Luxembourg	LUX	Serbia	SRB
Antigua	ATG	Ecuador	ECU	Macao SAR	MAC	Seychelles	SYC
Argentina	ARG	Egypt	EGY	Madagascar	MDG	Sierra Leone	SLE
Armenia	ARM	El Salvador	SLV	Malawi	MWI	Singapore	SGP
Aruba	ABW	Eritrea	ERI	Malaysia	MYS	Slovakia	SVK
Australia	AUS	Estonia	EST	Maldives	MDV	Slovenia	SVN
Austria	AUT	Ethiopia	ETH	Mali	MLI	Somalia	SOM
Azerbaijan	AZE	Fiji	FJI	Malta	MLT	South Africa	ZAF
Bahamas	BHS	Finland	FIN	Mauritania	MRT	South Sudan	SDS
Bahrain	BHR	France	FRA	Mauritius	MUS	Spain	ESP
Bangladesh	BGD	French Polynesia	PYF	Mexico	MEX	Sri Lanka	LKA
Barbados	BRB	Gabon	GAB	Monaco	MCO	Sudan	SUD
Belarus	BLR	Gambia	GMB	Mongolia	MNG	Suriname	SUR
Belgium	BEL	Georgia	GEO	Montenegro	MNE	Swaziland	SWZ
Belize	BLZ	Germany	DEU	Morocco	MAR	Sweden	SWE
Benin	BEN	Ghana	GHA	Mozambique	MOZ	Switzerland	CHE
Bermuda	BMU	Greece	GRC	Myanmar	MMR	Syria	SYR
Bhutan	BTN	Greenland	GRL	Namibia	NAM	Taiwan	TWN
Bolivia	BOL	Guatemala	GTM	Nepal	NPL	Tajikistan	TJK
Bosnia and Herzegovina	BIH	Guinea	GIN	Netherlands	NLD	Thailand	THA
Botswana	BWA	Guyana	GUY	Netherlands Antilles	ANT	TFYR Macedonia	MKD
Brazil	BRA	Haiti	HTI	New Caledonia	NCL	Togo	TGO
British Virgin Islands	VGB	Honduras	HND	New Zealand	NZL	Trinidad and Tobago	TTO
Brunei	BRN	Hong Kong	HKG	Nicaragua	NIC	Tunisia	TUN
Bulgaria	BGR	Hungary	HUN	Niger	NER	Turkey	TUR
Burkina Faso	BFA	Iceland	ISL	Nigeria	NGA	Turkmenistan	TKM
Burundi	BDI	India	IND	Norway	NOR	Former USSR	USR
Cambodia	KHM	Indonesia	IDN	Gaza Strip	PSE	Uganda	UGA
Cameroon	CMR	Iran	IRN	Oman	OMN	Ukraine	UKR
Canada	CAN	Iraq	IRQ	Pakistan	PAK	UAE	ARE
Cape Verde	CPV	Ireland	IRL	Panama	PAN	UK	GBR
Cayman Islands	CYM	Israel	ISR	Papua New Guinea	PNG	Tanzania	TZA

(*continued on next page*)

Table B (*continued*)

Country	Code	Country	Code	Country	Code	Country	Code
Central African Republic	CAF	Italy	ITA	Paraguay	PRY	USA	USA
Chad	TCD	Jamaica	JAM	Peru	PER	Uruguay	URY
Chile	CHL	Japan	JPN	Philippines	PHL	Uzbekistan	UZB
China	CHN	Jordan	JOR	Poland	POL	Vanuatu	VUT
Colombia	COL	Kazakhstan	KAZ	Portugal	PRT	Venezuela	VEN
Congo	COG	Kenya	KEN	Qatar	QAT	Viet Nam	VNM
Costa Rica	CRI	Kuwait	KWT	South Korea	KOR	Yemen	YEM
Croatia	HRV	Kyrgyzstan	KGZ	Moldova	MDA	Zambia	ZMB
Cuba	CUB	Laos	LAO	Romania	ROU	Zimbabwe	ZWE
Cyprus	CYP	Latvia	LVA	Russia	RUS		
Czech Republic	CZE	Lebanon	LBN	Rwanda	RWA		
Cote dIvoire	CIV	Lesotho	LSO	Samoa	WSM		

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